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Debonding Identification In FRP-plated RC structures using PZT sensors

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ABSTRACT: The application of the Electro-Mechanical Impedance (EMI) method for damage detection in Structural Health Monitoring has noticeable increased in recent years. EMI method utilizes piezoelectric transducers for directly measuring the mechanical properties of the host structure, obtaining the so called impedance measurement, highly influenced by the variations of dynamic parameters of the structure. These measurements usually contain a large number of frequency points, as well as a high number of dimensions, since each frequency range swept can be considered as an independent variable. That makes this kind of data hard to handle, increasing the computational costs and being substantially time-consuming. In that sense, the Principal Component Analysis (PCA)-based data compression has been employed in this work, in order to enhance the analysis capability of the raw data. Furthermore, a Support Vector Machine (SVM), which has been widespread used in machine learning and pattern recognition fields, has been applied in this study in order to model any possible existing pattern in the PCA-compress data, using for that just the first two Principal Components. Different known non-damaged and damaged measurements of an experimental tested beam were used as training input data for the SVM algorithm, using as test input data the same amount of cases measured in beams with unknown structural health conditions. Thus, the purpose of this work is to demonstrate how, with a few impedance measurements of a beam as raw data, its healthy status can be determined based on pattern recognition procedures.

KEY WORDS: *Strengthening with FRP; Damage; PZT; Impedance*.

1 INTRODUCTION

Civil infrastructures are continuously subjected to all kind of both static and dynamic loads, as well as severe environments, which can lead the structure under consideration to gradual deterioration and damage. For that reason, developing reliable Structural Health Monitoring (SHM) technologies has become a very important challenge in civil engineering. In particular, there has been an increasing interest on the Electro-Mechanical Impedance (EMI) method as one of the latest and most successful in the SHM field. This method uses piezoelectric transducers, such as piezoceramics (PZT), for directly measuring the mechanical properties of the host structure, obtaining the so called impedance measurement, highly influenced by the variations of dynamic parameters of the structure (Yang et al. [1], Saafi et al. [2], Min et al. [3]). These PZTs are both sensors and actuators that excite the host structure with a high frequency sweep, allowing one to compare the results of different measurements, and determining thus the damage developed between one health state and the one after the actuation of a certain load.

Furthermore, in combination with the different SHM methods, strengthening and retrofitting techniques using advanced composite materials are gaining widespread acceptance in recent years. Among those novel strengthening techniques, the use of external bonded strips made of Fibre-Reinforced Plastics (FRP) has many advantages over traditional techniques, since their high strength and modulus of elasticity, low weight and improve durability can enhance the behavior of the structure being strengthened (Bank [4]).

However, the use of the EMI methodology described above have the drawback of generating big amounts of data that need to be processed and analyzed. Dealing with this high-dimensional data can result in very inefficient and time-consuming procedures, in which most of the times, more data than needed are being used. In order to avoid these difficulties, measured data have been compressed in this paper by applying the Principal Component Analysis (PCA) algorithm, so just the data containing the higher influence in the results are used, neglecting the rest of them. The selected components will be, in addition, those which are more sensitive to damage (Park et al. [5]).

Finally, a Support Vector Machine (SVM), which is one of the supervised learning based pattern recognition algorithms, has been used in this work so that the different damages can be clustered for every different case of the experimental study carried out.

2 ELECTROMECHANICAL IMPEDANCE-BASED METHOD FOR DAMAGE DETECTION

The Electromechanical Impedance- based (EMI) method uses an array of small piezoelectric sensors either attached or embedded into the host structure, being capable of working both as actuators and sensors. The basic concept of the EMI method is to excite the structure with a high-frequency band, most of the times between 10 KHz and 100 KHz as it can be seen in the literature, in order to monitor the changes of the structural impedance of the local area of the structure where it has been placed.

The impedance of a structure, $Z_s(\omega)$, was firstly proposed by Liang et al. ([6]) as the inverse of the admittance, $Y(\omega)$, of the structure, defined as follows:

$$\begin{aligned} Y(\omega) &= \frac{I_0}{V_i} = G(\omega) + jB(\omega) = \\ &= j\omega a\left(\bar{\varepsilon}_{33}^{T} - \frac{Z_s(\omega)}{Z_s(\omega)+Z_a(\omega)} d_{3x}^2 \bar{Y}_{xx}^{E}\right) \end{aligned} \tag{1}$$

where V_i is the input voltage to the PZT actuator; I_0 the output current from the PZT; a, $\bar{\varepsilon}_{33}^{T}$, d_{3x} and $\bar{Y}_{xx}^{E}$ are the geometry constant, complex dielectric constant, piezoelectric coupling constant and complex Young's modulus of the PZT in a state without stresses, respectively; $Z_a(\omega)$ the impedance of the PZT actuator.

From this expression it can be extracted that the impedance of the host structure is directly related to the impedance of the attached/embedded PZT sensor, so it can be determined from the measurements made with the PZT sensor. It has to pointed out that, since the admittance is a complex number, so the impedance will be, and it has been proved (Park et al. [7]) that the real part of the impedance measurement is more sensitive to structural changes. So through different impedance measurements, it can be tracked the evolution of the changes in the structure, simply by a direct comparison between one state of the structure and the baseline, or even the immediate previous one.

However, damage (or incipient damage) cannot be determined through a direct comparison of impedance measurements of different health states, since these impedance values constitute just the electro-mechanical response of the structure to an input excitation. Thus, this provides only a qualitative assessment for the structural damage. For this reason, several statistical measurements and scalar metrics have been proposed in the literature for damage assessment. Among all of them, the Root Mean Square Deviation (RMSD) and the Cross-Correlation coefficient (CC) have been found to be the most efficient damage indicators (Peairs et al. [8]). These metrics can be formulated as follows:

$$RMSD(\%) = \sqrt{\frac{\sum_{i=1}^{n}\left[\operatorname{Re}\left(Z_0(\omega_i)\right) - \left(\operatorname{Re}\left(Z_1(\omega_i)\right)\right)\right]^2}{\sum_{i=1}^{n}\operatorname{Re}\left(Z_0(\omega_i)\right)^2}} \times 100 \tag{2}$$

$$CC = \frac{1}{n}\sum_{i=1}^{n}\frac{\left[\operatorname{Re}\left(Z_0(\omega_i)\right) - \bar{Z}_0\right]\left[\operatorname{Re}\left(Z_1(\omega_i)\right) - \bar{Z}_1\right]}{\sigma_{Z_0}\sigma_{Z_1}} \tag{3}$$

where $Z_0(\omega)$ is the impedance value in the state considered as healthy, which constitutes the baseline for the study, $Z_1(\omega)$ is the impedance value in the state to be studied (most of the times considered as damaged); σ_{Z_0} and σ_{Z_1} are the standard deviations of the real part of the impedances; $\bar{Z}_0$ and $\bar{Z}_1$ are the mean values of the impedance signals of $Z_0(\omega)$ and $Z_1(\omega)$. The RMSD metric is commonly given as a percentage value (Yang et al. [1]) that increases with the damage increase, while the CC metric decreases when the different between the damage state and the undamaged state increases. For convenience, in the case of the CC metric, the feature examined is usually $(1-CC)$ to ensure that the damage metric value increases with increasing change in structure integrity. Furthermore, it has been found that this feature shows a better damage indication when using its third-order exponent: $(1-CC)^3$, so this metric will be used instead of just the Cross-Correlation coefficient.

These indices are more commonly used to assess the structural damage of the structure under consideration, in comparison with the predefined baseline of the structure. But they can also be used to assess the evolution of the damage between two different health states (with damage at different points of development), obtaining thus a measure of damage increase between them.

3 PRINCIPAL COMPONENT ANALYSIS FOR DATA COMPRESSION

Principal Component Analysis (PCA) is a statistical technique that reduces the dimensionality of a data set containing a large number of interrelated variables, while retaining as much as possible of the variation present in the original data set (Jolliffe, [9]). In order to achieve this, a linear transformation has to be done, performing an orthogonal projection to a new variable space, resulting on a new set of uncorrelated variables called Principal Components (PCs), and which are ordered so that the first few of them preserve most of the variation present in the original variables. Therefore, the original set can be represented with a linear combination of just a few of its variables, reducing the dimension of the problem.

Furthermore, PCA technique focuses on variances in order to obtain the PCs. Since these PCs constitute a representation of the "principal axes" in the new space, they can be obtained through a Singular Value Decomposition (SVD) of the covariance matrix (Park et al. [5]). Given the measurement data sets:

$$\begin{gathered} \{x\}_j = \{x_{j1}, x_{j2}, \ldots, x_{jn}\} \\ j = 1, 2, \ldots, m \end{gathered} \tag{4}$$

where n is the number of variables, and m the number of measurements contained in each variable, the covariance matrix can be defined as follows:

$$[C] = \sum_{j=1}^{m}\{x\}_j\{x\}_j^T \tag{5}$$

and the SVD procedure results on the following:

$$[C] = [A][\Lambda][A]^T \tag{6}$$

where $[\Lambda]$ is a diagonal matrix containing the eigenvalues of the covariance matrix, and $[A]$ the matrix containing the corresponding eigenvectors. With this expression, the PCs can be finally formulated as follows:

$$\{z\}_j = [A]^T \left(\{x\}_j - \{\bar{x}\}\right) \tag{7}$$

where $\{\bar{x}\}$ is the vector of means of the x-data. Since the eigenvalues are sorted in descending order, so the PCs are, having the first few of them all the variation which is interesting for the study.

In this work, the EMI method has been applied performing a frequency sweep between 10 KHz and 100 KHz, which results on a large set of data that can be reorganized as a set of nine variables (10 KHz per variable), having in this way nine dimensions to deal with in order to assess the structural damage. At this point, PCA method has been applied in order to reduce the dimensionality of the problem, so that, in most of the cases, the first two or three principal components have been enough to reconstruct the original impedance values. By performing this reduction, the new data set is much easier to understand and use, and also the noise usually contained in the raw data can be easily erased, which can result in a better damage prediction.

4 SUPPORT VECTOR MACHINE ORIENTED TO SHM

Support Vector Machines (SVMs) are a useful technique for data classification, especially in the SHM field. As linear classifiers, they are especially suitable for two-class linearly separable tasks (Theodoridis et al. [10]), which usually involves separating data into training and testing sets (Bornn et al. [11]). All data in the training set is associated to a "target value" (usually a 0 or a 1, based on the *all vs one* theory, that separates the data into two subsets: the target one and the rest), besides several characteristic "attributes" or parameters extracted from the compressed data. The goal of the SVM algorithm is, thus, to create a model that predicts the target value corresponding to the test data given only its characteristic attributes, which have to be the same number and the same nature as the training attributes.

Since it usually happens that the sets to be classified are not linearly separable in their current finite dimensional space, the process consists on firstly project the test data to a higher dimension space, in which dot products will be computed as easily as in the previous space. In order to achieve that transformation, a kernel function is used to suit the problem. Several kernel functions have been proposed in the literature, but the following ones could be considered as the most common ones in this kind of problems:

- Linear:

$$K\left(x_i, x_j\right) = x_i^T x_j \tag{8}$$

- Polynomial:

$$K\left(x_i, x_j\right) = \left(\gamma x_i^T x_j + r\right)^d, \ \gamma > 0 \tag{9}$$

- Radial Basis Function (RBF):

$$K\left(x_i, x_j\right) = \exp\left(\gamma \left\|x_i^T - x_j\right\|^2\right), \ \gamma > 0 \tag{10}$$

- Sigmoid:

$$K\left(x_i, x_j\right) = \tanh\left(\gamma x_i^T x_j + r\right), \ \gamma > 0 \tag{11}$$

where x_i and x_j are two different training sets (with different target values to be compared); and r, γ and d are kernel parameters.

Once the projection of the training data set has been done, the goal is to find a hiperplane that classifies correctly the training vectors into the two different groups of data. This hiperplane is not unique, depending on different factors (Theodoridis et al. [10]), being one of those factors the selected kernel for the data projection. After selecting the appropriate hiperplane, it is projected back to the original space, together with the data sets, so that a line can be drawn in order to separate the two different data sets.

In this work, a SVM has been used in order to classify different damage cases, being the different kernel functions assessed. The algorithm has been used not only to distinguish between a damaged state and an undamaged one, but also between damaged cases with different severities.

5 EXPERIMENTAL RESULTS

5.1 FRP-Strengthed specimens

In order to evaluate the methodology proposed in this paper, some tests were performed on several concrete specimens (Figure 1) strengthened with FRP with different levels of damage by debonding (Figure 2, where sensors are numbered from 1 to 5 from left to right).

These specimens were firstly made of concrete, being the dimensions 31.3 cm length, 9.5 cm width and 7.5 cm depth. After waiting for twenty eight days, so that the concrete could reach its maximum strength, the external reinforced was applied by bonding a FRP strip for flexural strengthening (29.5 cm length, 5 cm width and 0.18 cm depth).

Figure 1. Concrete FRP-strengthened specimen.

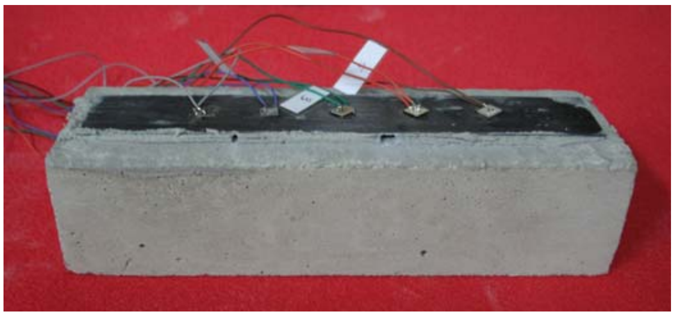

Figure 2. Damage by debonding.

5.2 Description of the experiment

Five PZT sensors were attached to the reinforced concrete specimen in the way it can be seen in Figure 2. These sensors were connected to an impedance analyzer.

A first test was performed, without any damage in the specimen, developing a frequency sweep from 10 KHz to 100 KHz. The bandwidth of the sweep was adjusted to make point averaging, so that noise is almost erased from all measurements, in order to obtain a more reliable result. Furthermore, 5 full sweeps were developed per sensor and damage case, and the average of each of them was use as raw data for further analysis. After the first case without any damage, which can be considered as a baseline for the experiment, three more damage scenarios were measured within the same frequency ranges:

- First Damage: a 5 mm debonding in the middle of the specimen, between the sensor number 3 and the sensor number 4 (slightly closer to the debonding).
- Second Damage: amplification of the debonding practiced in the prior stage to 1 cm (right debonding in Figure 2).
- Third Damage: a new 5 mm debonding between the sensor number 1 and the sensor number 2 (left debonding in Figure 2)

These raw data were then subjected to dimension reduction with the Matlab's toolbox for the PCA procedure. In each damage case (and in each sensor), the number of PCs selected for data reconstruction is different depending on the amount of variation present in the original variables that the PCs can represent, information that is provided by the toolbox itself. For instance, in the case of the sensor number 4 with no damage, three PCs are needed (Figure 3), while four are needed in the second stage of damage (Figure 4).

In both figures, the reconstructed data experiment a vertical shift respect to the original data, which is due to the PCA process itself, in which the average of the raw data is subtracted when reducing the data's dimension.

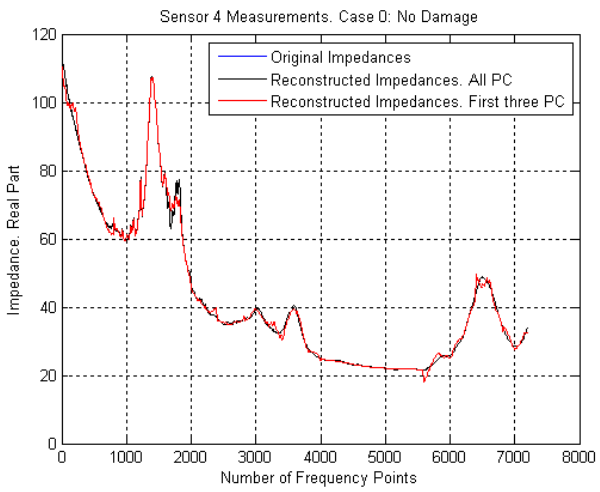

Figure 3. Sensor 4: No damage data reconstruction

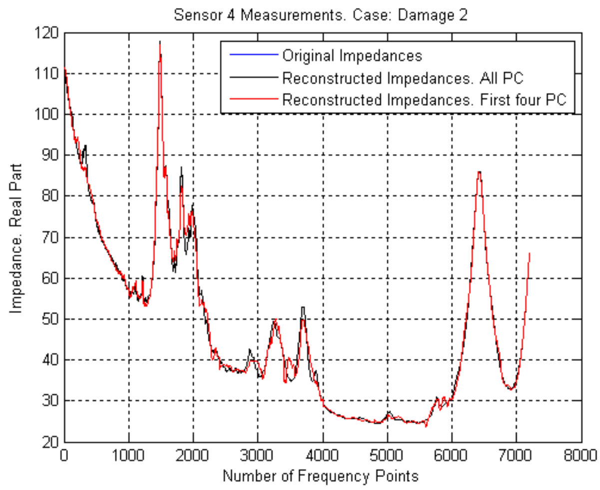

Figure 4. Sensor 4: Second stage of damage data reconstruction

From these processed and compressed data, damage indices commented in Section 2 were calculated for the following cases:

- First stage of damage for all the sensors, in comparison to the baseline or undamaged state.
- First, second and third stages of damage for sensor number 4, in comparison to the respective prior state, in order to show the evolution of the damage indices through different damage states.

Finally, a classification of the different damage cases for the sensor 4 has been made, using for that the Matlab's toolbox for SVM classification.

5.3 Experimental results: scalar metrics

Both damage indices were calculated as commented above, being shown at Table 1 and Table 2, where the damage increments between several damage stages are shown (0 – Baseline; 1 – First Damage; 2 – Second Damage).

Table 1. RMSD metric results.

RMSD (%)	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
0 → 1	2.58	3.02	3.07	17.05	2.34
1 → 2	-	-	-	17.18	-
2 → 3	-	-	-	10.25	-

Table 2. $(1-CC)^3$ metric results.

$(1-CC)^3$ (%)	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
0 → 1	99.958	99.958	99.959	99.966	99.959
1 → 2	-	-	-	99.965	-
2 → 3	-	-	-	99.96	-

These results are also shown in Figure 5 and Figure 6, respectively. Figure 5 shows the damage detected at each sensor in the first damage stage, explained above, using both scalar metrics. Here it should be pointed out, although the metric $(1-CC)^3$ shows a high indication of damage in all the sensors, which could be reasonable, it does not allow one to extract information about the severity or location of the damage, since the metric is the same in all the sensors. However, the RMSD shows a better damage indication, since it is only significant in the sensor number four, the one which is closer to the debonding. A similar indication could be expected at sensor number 3, which is also close to the damage, but the result is low instead.

Finally, Figure 6 shows the evolution of the damage in the sensor number 4 through the different stages, using again both scalar metrics. The metric based on the CC shows, once again, damage in all sensors without any difference, which makes impossible to determine the location and severity of the damage. However, the RMSD provides useful information about the damage evolution. The first two indications are quite similar due to the location and severity of the damage at both stages, which are almost the same, and the third one is slightly smaller, because in this stage de debonding was originated farther from sensor 4. Here it is worth it to point out that all the indications represent a damage increment in terms of percentage.

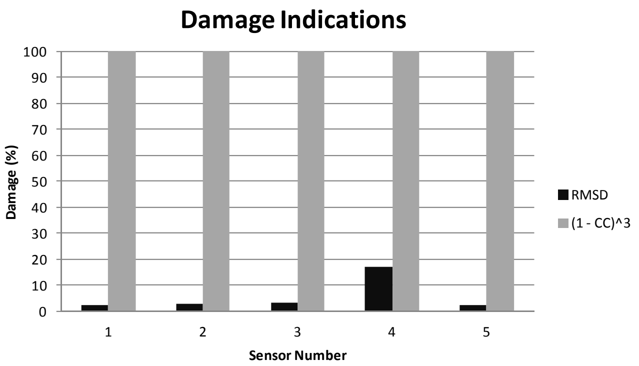

Figure 5. Scalar metrics for damage assessment

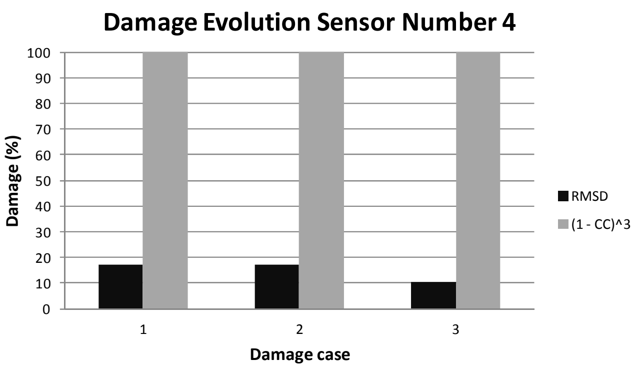

Figure 6. Damage evolution at sensor number 4

5.4 *Experimental results: damage cases' classification*

As commented above, a SVM has been used in order to classify different damage cases, using for that the Matlab's toolbox for SVM classification.

The algorithm has been used not only to distinguish between a damaged state and an undamaged one, but also between damaged cases with different severities. In that sense, four different states have been chosen: the non-damaged state (baseline) and the other three explained above. For every case, two measurements were taken for training and another two for testing (eight testing sets, being the test sets known, but treated as unknown in order to assess this procedure). Furthermore, six parameters (maximum value, minimum value, mean value, standard deviation, RMSD -%- metric and CC -%- metric) were selected in order to characterize each damage case, so that the SVM can correctly classify each case in the appropriate group. Thus, both the training and test sets are 8x6 matrices.

The classification procedure, based on the *one versus all* theory, was carried out checking all the kernel functions detailed above, achieving the best classification when using the *quadratic* kernel function. With this kernel function, and using the six parameters for all the cases, a perfect classification was achieved for the eight testing sets, resulting on a 0% error prediction in all the cases. It is important at this point to highlight that damage has been predicted accurately in all the cases, which means that no false alarms or missed detection cases were found.

Since each case has six parameters, the results cannot be represented in a graphic that clearly shows how well this procedure distinguishes between each damage case. However, it turns out that after the prediction has been made by the SVM algorithm, a 3D representation can be plotted selecting three of these parameters each time, as shown in Figure 7 and Figure 8.

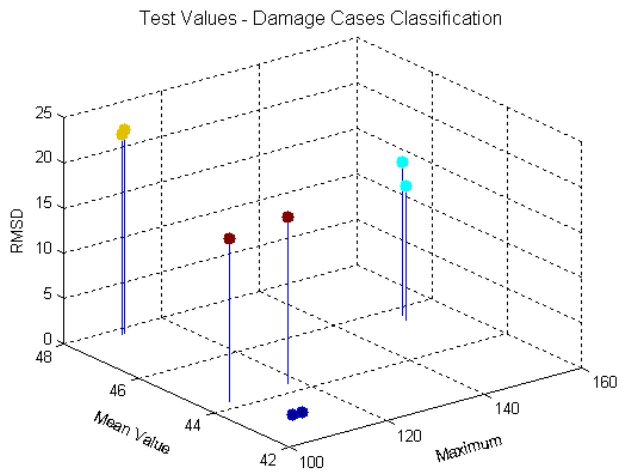

Figure 7. Damage prediction. Maximum, mean and RMSD values.

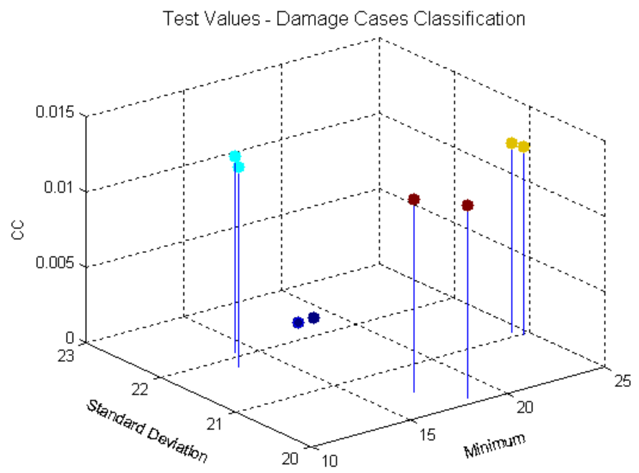

Figure 8.Damage evolution at sensor number 4

In both figures it can be seen how the eight testing cases (two cases per damage stage) are perfectly distinguished, assigning a different color to each debonding case.

6 CONCLUSIONS

A procedure for damage cases identification and classification has been proposed in this paper, based on pattern recognition methods. This procedure has been successfully developed and assessed to detect debondings between the laminate and concrete of FRP-strengthened concrete specimens. A compression data technique has also been used in order to reduce data dimension, achieving at the same time a noise reduction in the raw data.

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